BCF 2023
BALTIC CARBON FORUM

BASRECCS

EXPLORING CO2 STORAGE POTENTIAL IN LITHUANIAN DEEP SALINE AQUIFERS USING DIGITAL ROCK VOLUMES: A MACHINE LEARNING GUIDED APPROACH

Shruti Malik[1], Pijus Makauskas [1], Ravi Sharma[2] and Mayur Pal [1]

[1] Kaunas University of Technology, Dept. of Mathematical Modelling, Kaunas, Lithuania

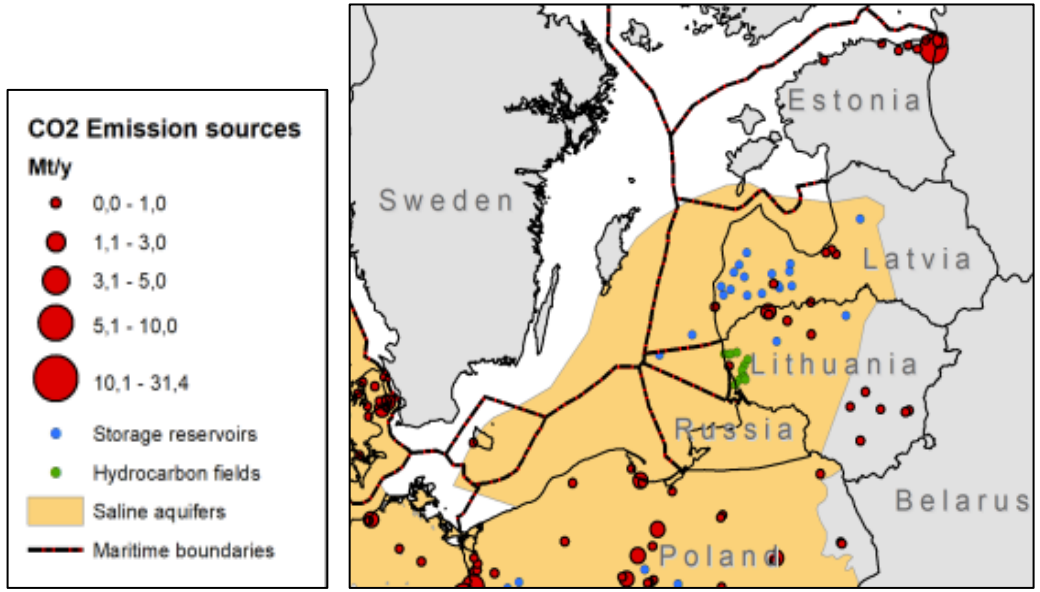
[2] Dept. of Earth Sciences, Indian Institute of Technology Roorkee, India

OUTLINE

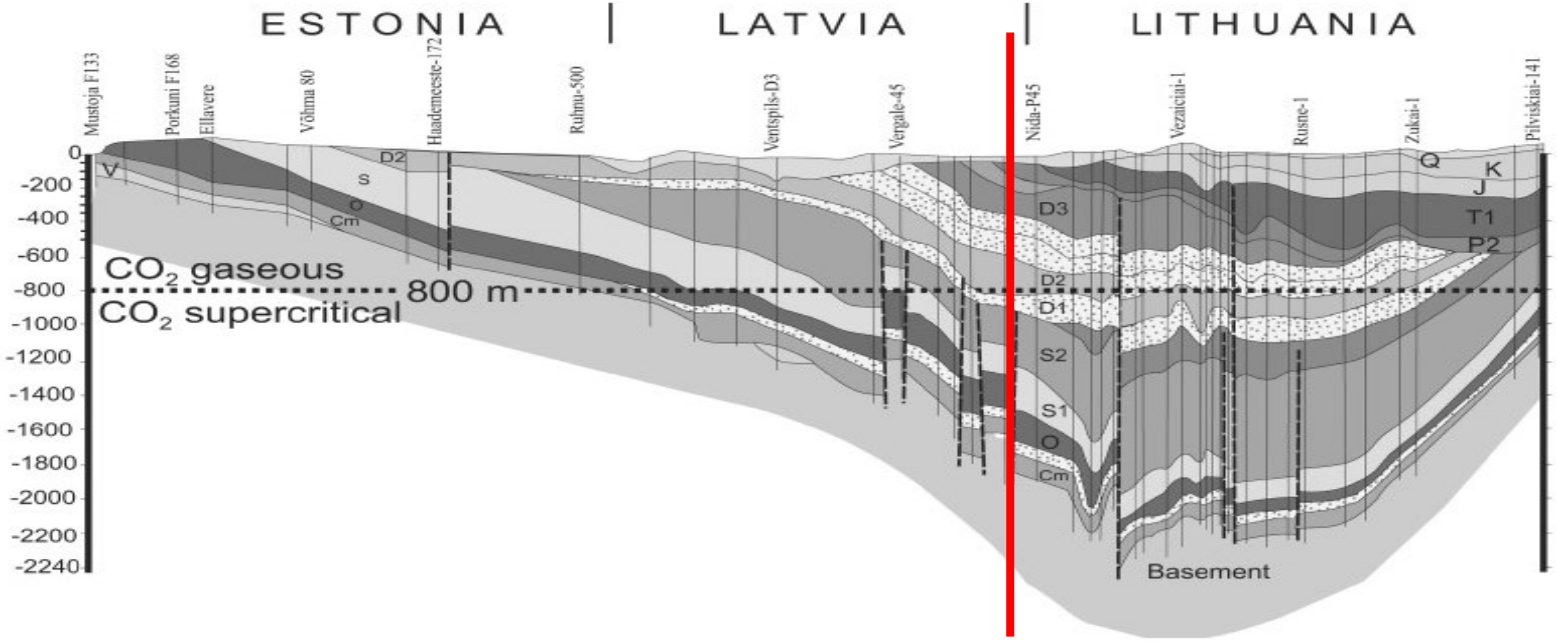
- Introduction
- Motivation
- Objectives
- Laboratory Measurements
- Sample Description
- Methodology
- Results
- Conclusion and Future Work
- Acknowledgement
- References

BALTIC BASIN

- Extends in countries such as Lithuania, Latvia, and Estonia;
- It has several hydrocarbon and deep saline reservoirs in offshore and onshore settings.
- These reservoirs comprise of both sandstone and carbonate rocks



© Geological Survey Of Denmark And Greenland

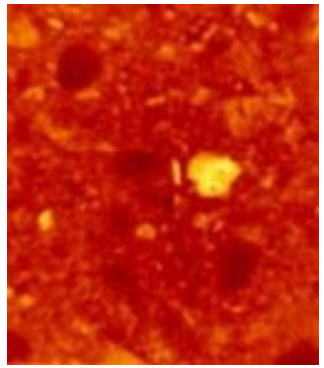


(Shogenova et al., 2009)

DIGITAL ROCK PHYSICS (DRP)

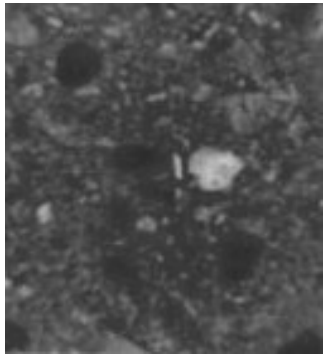
Optical Image

Scanning at Multiscale resolution



CT scan Image

Filtering for improved S/N



8 bit Image

Thresholding

Segmented Image

Flow simulation

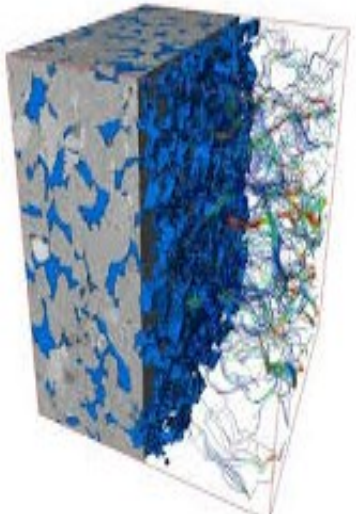


Image showing the pore network

MOTIVATION

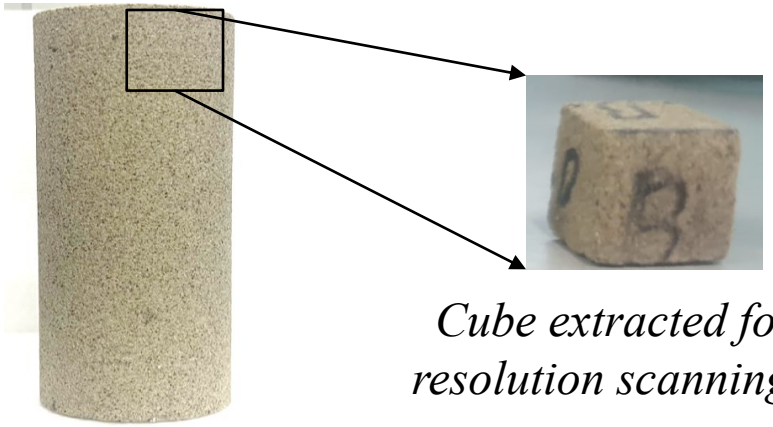
- CO_2 emissions are on rise globally and there is an emergent need to curb carbon emissions to mitigate the risks associated with climate change.
- Carbon Capture, Utilization and Storage (CCUS) is considered one of the effective methods.
- All fluid storage and flow processes in the subsurface lithological formations occur essentially at pore scale level; therefore, it is imperative to have a closer look at the processes and physics of storing CO_2 over long periods and its impact on the integrity of the lithological formation.
- Digital Rock Physics offers a non-destructive and efficient method for investigating pore-scale processes and characterizing a reservoir in terms of long-term CO_2 storage.

OBJECTIVES

- To understand the deep saline reservoirs of Lithuania using Micro Xray CT scanned images.
- To estimate the petrophysical parameters (porosity and permeability) of core sample.
  - Use machine learning methods to extract porosity.
  - Carry out lattice Boltzmann simulation to extract permeabilities from digital models.
- To extract a representative element volume (REV) of the core samples.
- To benchmark the methodology adopted on analogue samples, enabling its further application on reservoir samples.
- To assess the storage capacity of the saline aquifers of Lithuania.

LABORATORY MEASUREMENTS

- Scanning of the core samples: Micro Xray-Computed Tomography (MXCT) scans were obtained using Skyscan 1275 © Bruker.
- Scanning resolution: The samples are scanned at two different resolutions, low resolution (22um) and high resolution (8um).



Cube extracted for high resolution scanning (8um)

Core sample for low resolution scanning (22um)

Figure: Instrument used for scanning core samples

SAMPLE DESCRIPTION: SAMPLE SET 1

- Sandstone samples, primarily composed of quartz as the dominant mineralogy with minor occurrences of clay minerals, analogous to Lithuanian reservoirs.

Sample name	Porosity (%)	Permeability (mD)
S1	21.60	275
S2	19.90	62
S3	20.22	327

S1

S2

S3

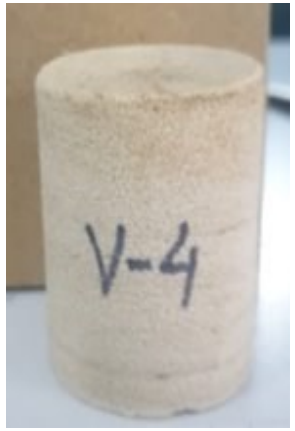
SAMPLE DESCRIPTION: SAMPLE SET 2

- Sandstone samples from actual Lithuanian reservoirs

Reservoir Type	Reservoir Name	Sample Name	Porosity (%)	Permeability (mD)
Deep saline aquifer	Syderiai	S3	16	246
	Vaskai	V4	22	1308

S3

V4



METHODOLOGY ADOPTED

Part I:

Reservoir Characterization

Micro Xray CT scan of the core samples

Image processing

Segmentation using k-means algorithm

Sub-volume extraction

Flow simulation using LBM

SAMPLE SETS

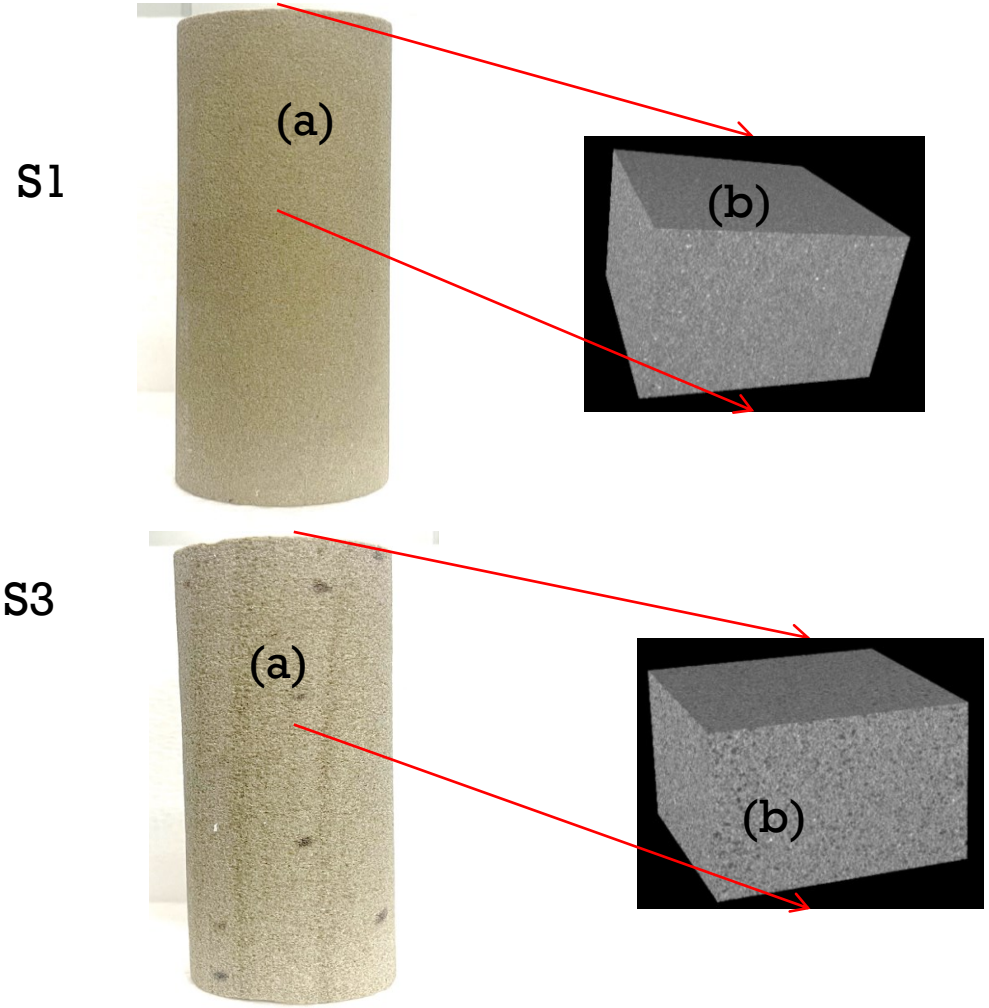
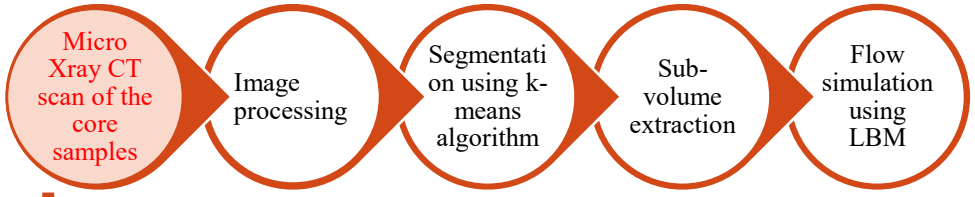


Figure: (a) A core sample with length = 2.5inch and diameter = 1.5inch and, (b) raw 3D volume generated from MXCT imaging at resolution of 22um. The 3D volume size is 941 X 941 X 601 pixels.



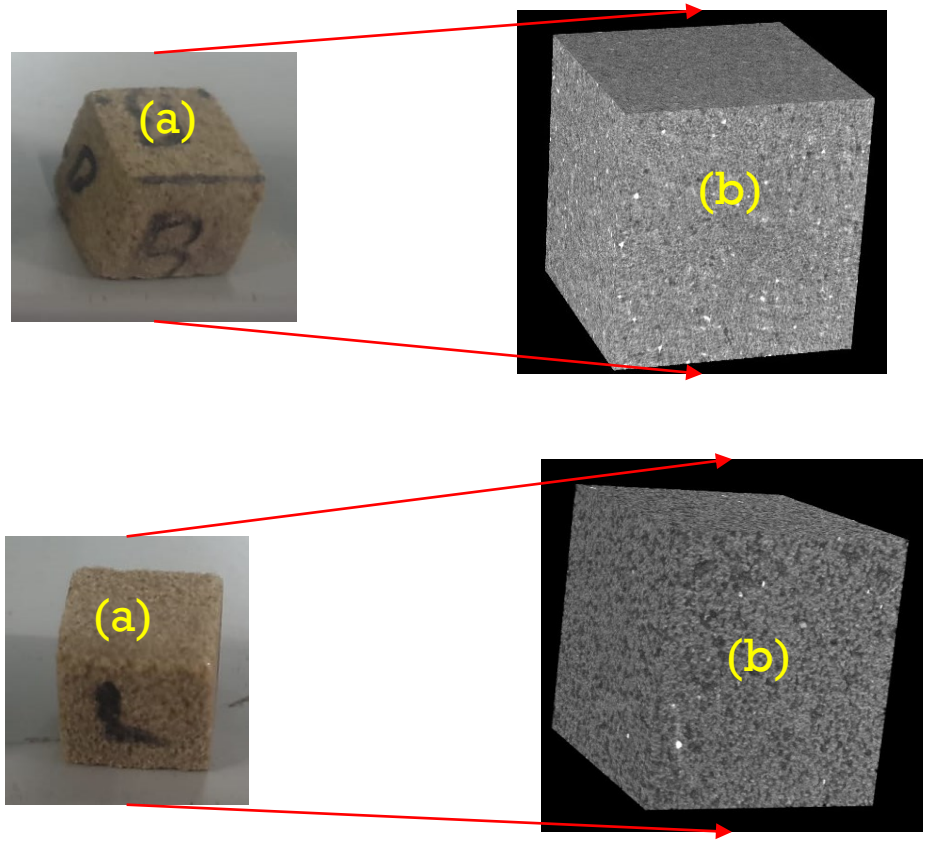
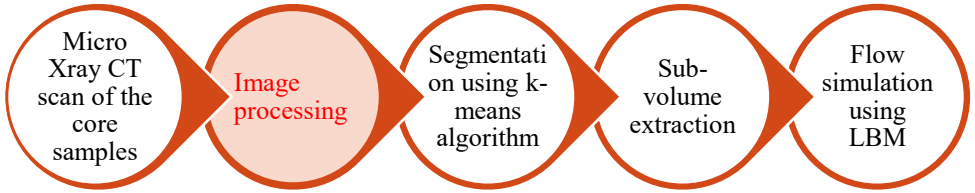
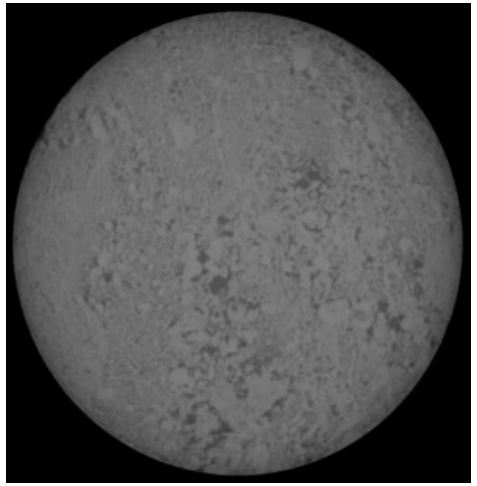


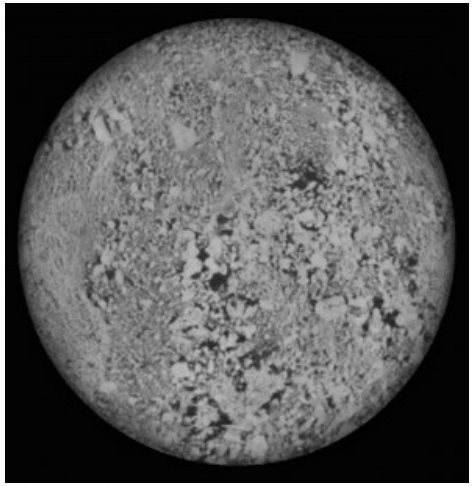
Figure: (a) A sample cube of 2cm, (b) raw 3D volume generated from MXCT imaging at resolution of 8um. The 3D volume size is 1020 X 1020 X 1014 pixels.

RESULTS: IMAGE PROCESSING



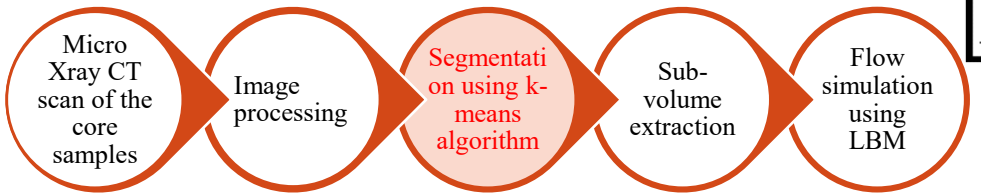


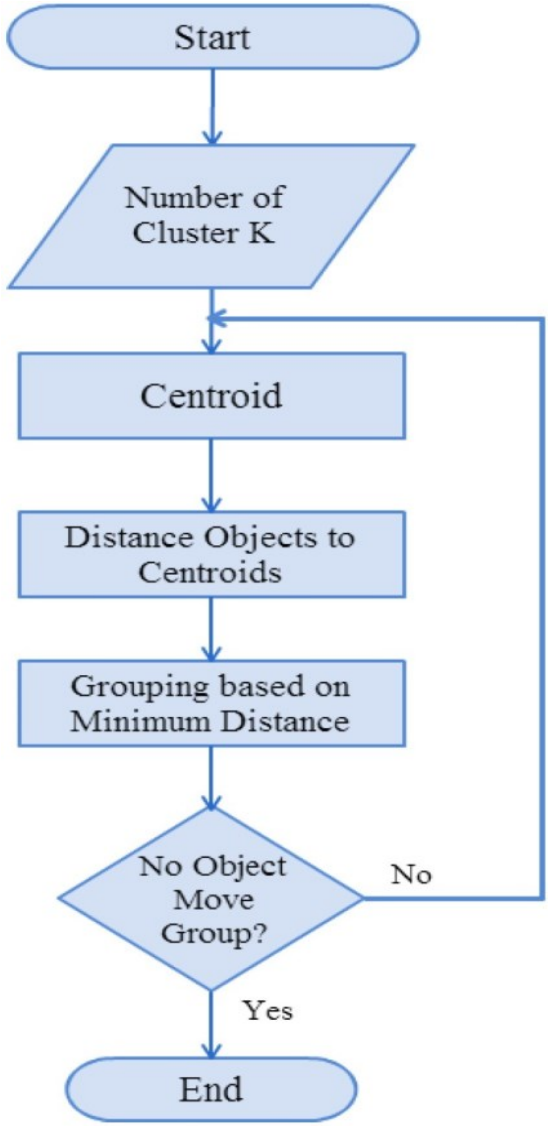
Original Image



Contrast Limited Adaptive Histogram Equalization (CLAHE) adjusted Image

SEGMENTATION: K-Means Algorithm





The objective function that is minimized is given by:

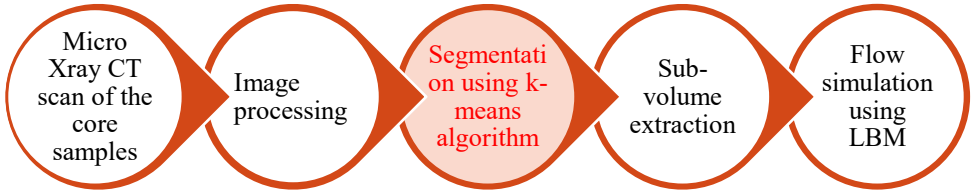
$$Z = \sum_{i=1}^{n} \sum_{j=1}^{k} \|x^{(i)} - C_j\|^2$$

Where, $\|x^{(i)} - C_j\|^2$ is the Euclidean distance between the data point x(i) and cluster centroid C*j*.

$$C_j = \frac{1}{n} \sum_{i=1}^{n} x_j^{(i)}$$

Where n is the number of data points in the *jth* cluster and $x_j^{(i)}$ is the ith data point.

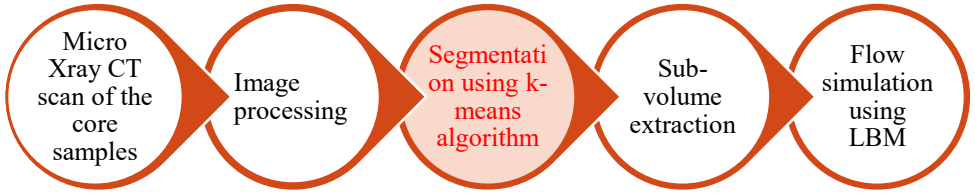
RESULTS: SAMPLE SET1



Sample	Porosity using K-means algorithm (%)	Laboratory measured porosity (%)	Error (%)
S1	19.98	21.6	7.5
S2	19.70	19.9	1.0
S3	19.99	20.22	1.1

Table: Benchmarking of the porosity values with laboratory measured values

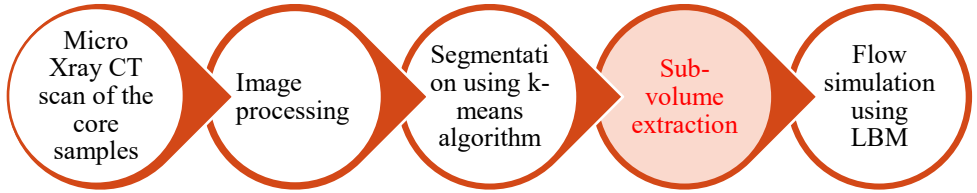
RESULTS: SAMPLE SET2



Sample Type	Sample	Porosity using K-means algorithm (%)	Laboratory measured porosity (%)	Error (%)
Core (22μm)	S3	14.38	16	10
	V4	19.74	22	10
Cube (8μm)	S3	15.17	16	5
	V4	23	22	4.5

Table: Porosity values of Lithuanian samples compared with laboratory measured values

RESULTS: EXTRACTION OF SUB-VOLUMES



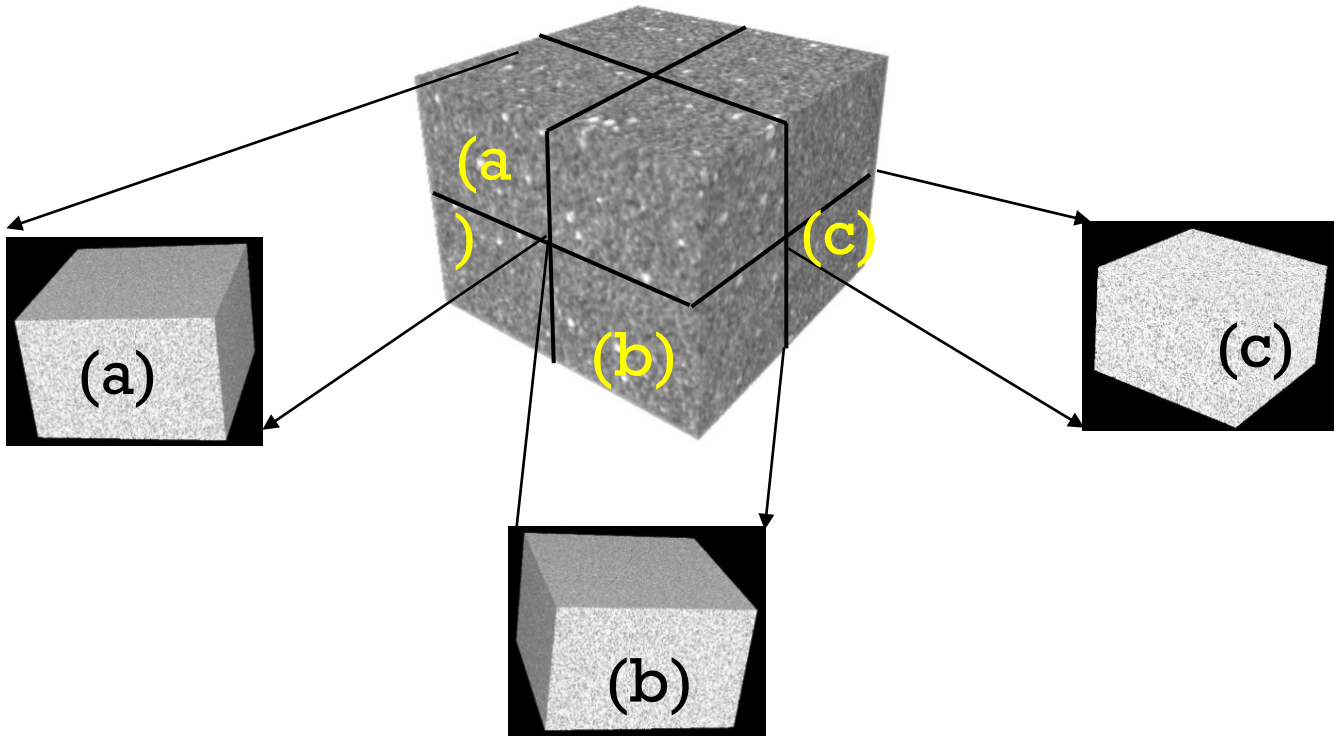
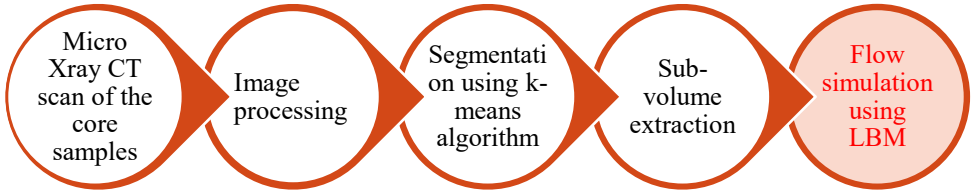


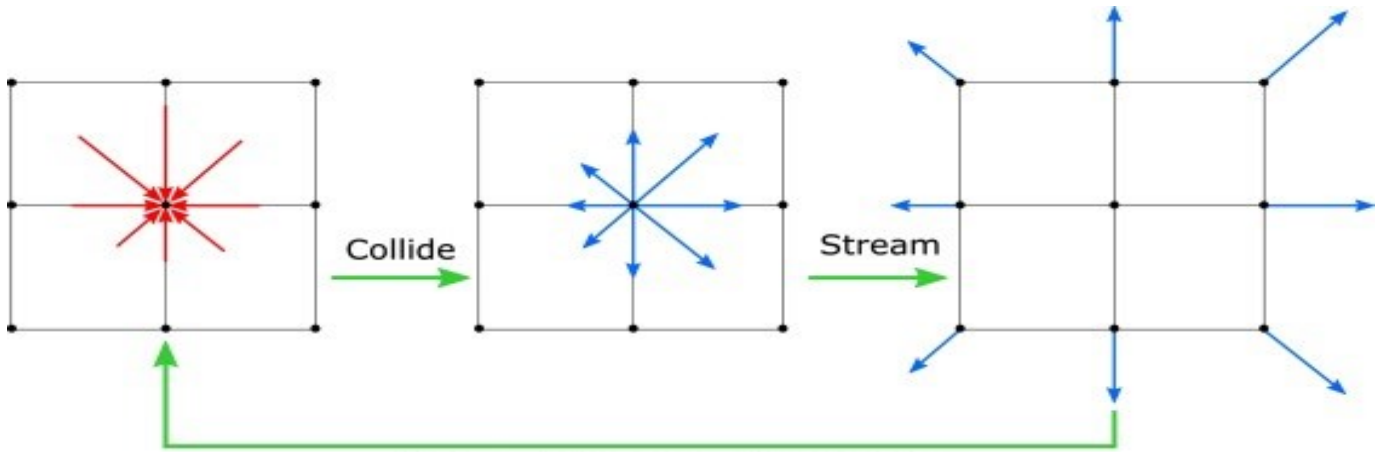
Figure: Illustration of the sub-volume extraction for fluid flow simulation

LATTICE BOLTZMANN METHOD



- In the LBM, fluid is considered as a collection of particles that are represented by a probability distribution function at each discrete lattice node. The Lattice Boltzmann equation updates the probability distribution function at each time step and from this the velocities are calculated.

- LBM has 2 main steps: collision and streaming



LATTICE BOLTZMANN METHOD (CONTD.)

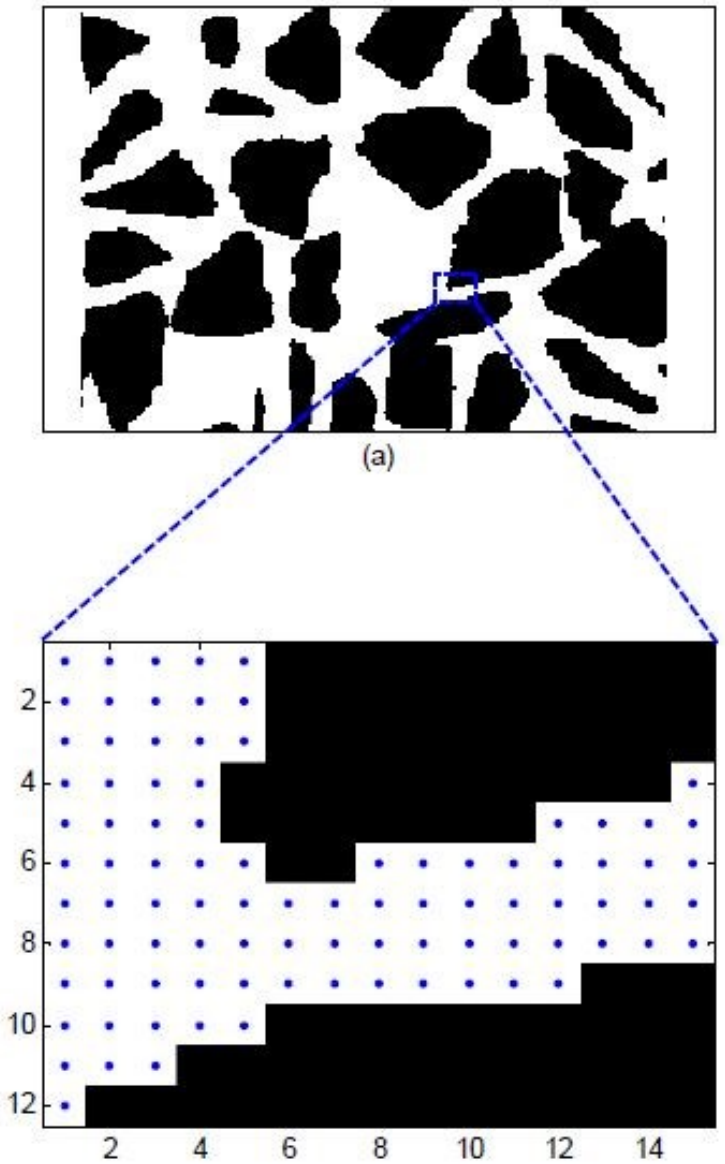
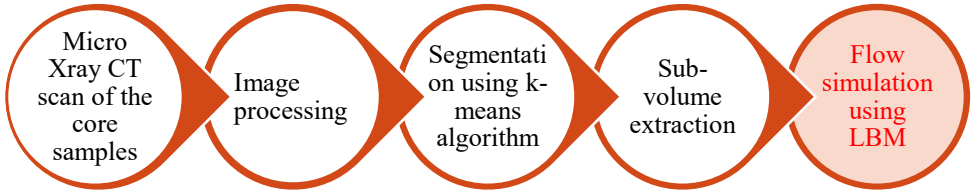


Figure: Binary image, where black area represents grains and white area representing the pores(above) and creation of lattice nodes at the center of each white pixel(bottom).

RESULTS (CONTD.)



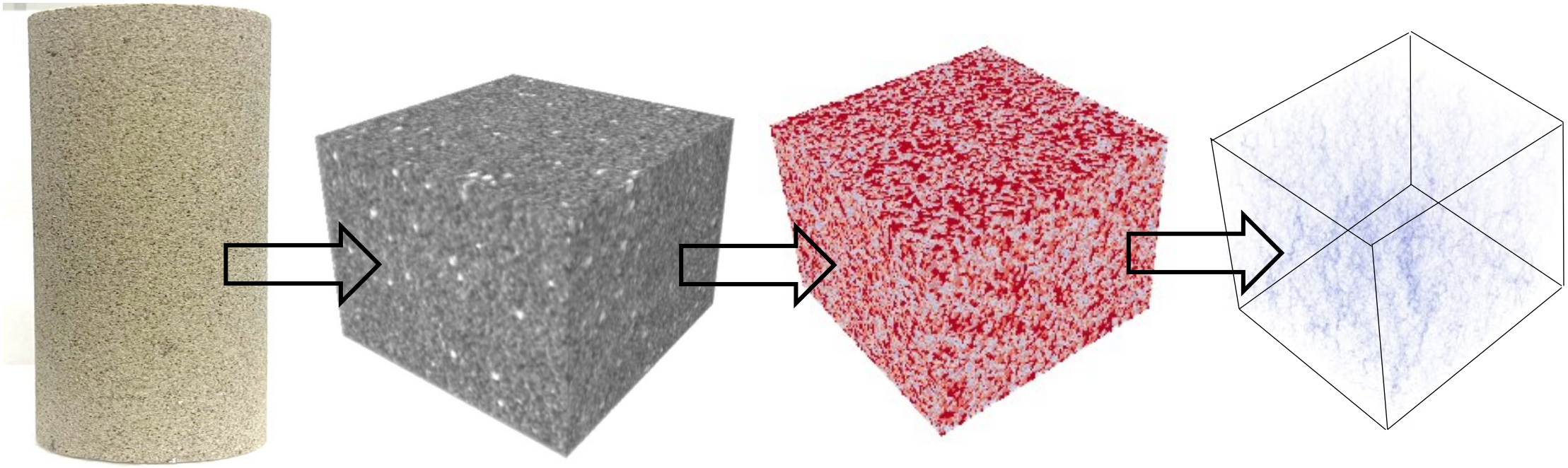
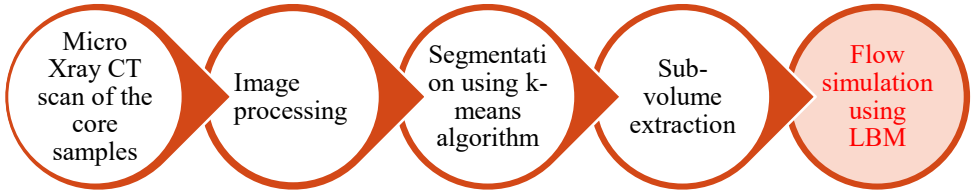


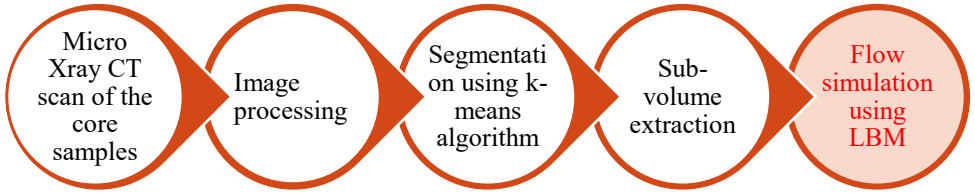
Figure: From left to right: Raw core sample, Scanned 3D volume, its segmented 3D volume and LBM simulated output, where blue thread like distribution shows the fluid flow through the pore space.

RESULTS: PERMEABILITY ESTIMATION (SAMPLE SET1)



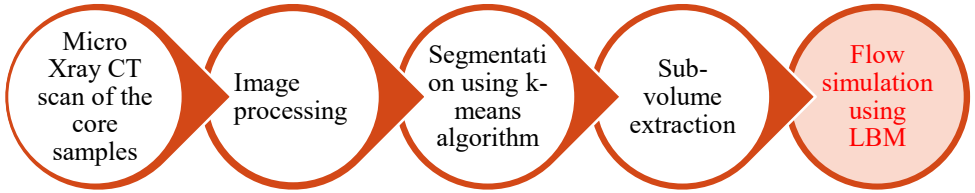
Sample	Sub-volumes (201X201X201)	Permeability using LBM (mD)	Average permeability (mD)	Laboratory (mD)	Error (%)
S1	1	282	317	275	15
	2	307			
	3	360			
	4	320			
S2	1	83	91	62	47
	2	105			
	3	100			
	4	77			
S3	1	445	370	327	13
	2	334			
	3	370			
	4	330			

RESULTS: PERMEABILITY ESTIMATION (SAMPLE SET2)



Sample	Sub-volumes (251X251X251)	Permeability using LBM (mD)	Average permeability (mD)	Laboratory (mD)	Error (%)
S3	1	244	272	246	10.5
	2	326			
	3	298			
	4	315			
	5	236			
	6	211			
V4	1	1129	1364	1309	4.2
	2	1668			
	3	1308			
	4	1209			
	5	1609			
	6	1259			

RESULTS: PERMEABILITY ESTIMATION (SAMPLE SET2)



Sample	Sub-volumes (251X251X251)	Permeability using LBM (mD)	Average permeability (mD)	Laboratory (mD)	Error (%)
S3 Cube	1	288	269	246	9.0
	2	320			
	3	187			
	4	280			
V4 Cube	1	1347	1313	1309	0.3
	2	1304			
	3	1269			
	4	1332			

METHODOLOGY ADOPTED

Part II:

Storage Capacity Assessment

3D mechanistic model

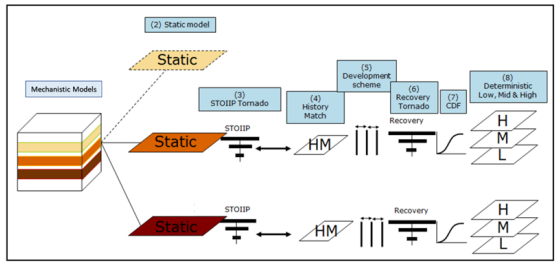
Define uncertainty ranges for reservoir parameters

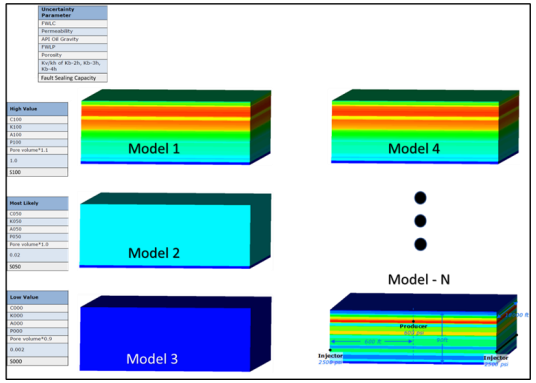
Define model dimensions uncertainty

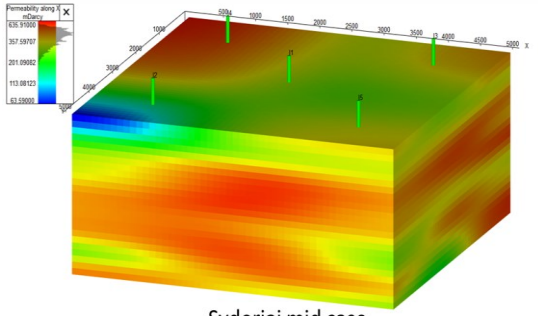
Perform simulation using CO2SOL option in T-navigator

Storage volume estimation

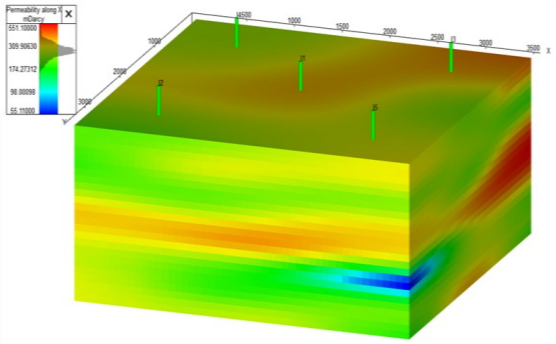
METHODOLOGY (CONTD.)







Syderiai mid case

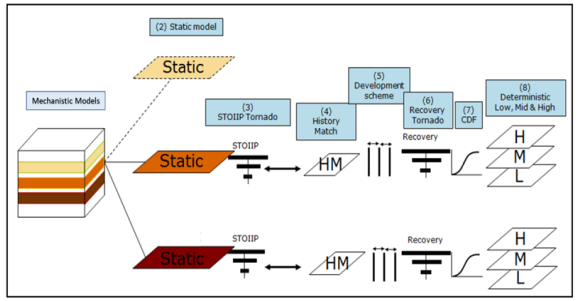


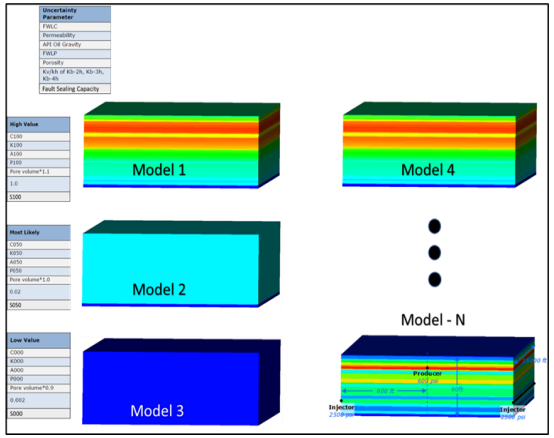
Vaskai mid case

	Syderiai				Vaskai		
	Low	Mid	High		Low	Mid	High
Porosity	0.144	0.16	0.208		0.207	0.23	0.299
Perm X	360	400	520		252	280	364
Perm Y	360	400	520		252	280	364
Perm Z	119.7	133	172.9		84	93.33	121.33
Thickness	51.3	57	74.1		51.3	57	74.1
NTG	0.675	0.75	0.975		0.45	0.5	0.65
AREA	23.4	26	33.8		11.07	12.3	15.99

Property Uncertainty high/mid/low

RE-EVALUATION METHODOLOGY





	Syderiai				Vaskai		
	Nx	Ny	Nz		Nx	Ny	Nz
	50	50	25		50	50	25
Lx	4837.3	5099.0	5813.7		3327.1	3507.1	3998.7
Ly	4837.3	5099.0	5813.7		3327.1	3507.1	3998.7
Lz	51.3	57	74.1		51.3	57	74.1
Dx	96.7	101.9	116.2		66.5	70.1	79.9
Dy	96.7	101.9	116.2		66.5	70.1	79.9
Dz	2.052	2.28	2.96		2.05	2.28	2.96
	Low	Mid	High		Low	Mid	High

Model dimensions Uncertainty high/mid/low

CONCLUSION

- Carbon Capture and Storage (CCS) is a potent method to reduce greenhouse gas emissions by capturing and storing carbon dioxide in subsurface reservoirs.
- Image based 3D quantification of the porosity and permeability helps to understand the distribution of pore space and the flow behavior in presence of different fluids, respectively.
- The porosity and permeability values agreed with the laboratory measured values. The relatively high percentage of error in permeability does not have a significant impact since we are considering the order of magnitude, which aligns accordingly.
- Digital Rock Physics can help in analyzing the reservoir behavior when injected with CO2 and in assessing the long-term storage capacity of a reservoir.

CONCLUSION (CONTD.)

- Large CO_2 storage potential exists within Lithuanian Cambrian reservoirs.
- 3D mechanistic models are used to evaluate the storage potential of the two main saline aquifers.
- The 3D numerical simulation results obtained using CO2SOL modelling option used in T-navigator combined with uncertainty modelling principles.
- Modelling results show that:
  - All three deep saline aquifers' combined capacity of CO_2 storage ranges from 347Mt – 1589Mt of CO_2.

FUTURE WORK

- This work can be extended to explore the associated implications for various aspects of long-term storage such as geochemical reactions, and geo-mechanical behavior of the rock which shall further aid in identification of reservoir(s) wherein sequestration possibilities can be reliably explored.

- Incorporating different subsurface uncertainties is possible during flow simulations to understand the impact of subsurface heterogeneity on fluid flow.

ACKNOWLEDGEMENT

- Lithuanian Research Council Funding for postdoctoral research fund Proposal registration No. P-PD-22-022-PATIKSLINTA.

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Thank you